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Optimizing Automotive Spare Parts Inventory: A Comparative Study of Quantitative Forecasting Techniques

[1]Hilal A. Abdelwali*, [1]Swilem A.M. Swilem, [1]Farraj Aldaihani, [2]Mohamed H. Abdelati
[1]Assistant Professor, Automotive and Marine Department, College of Technological Studies, PAAET, Kuwait.
[2]Automotive and Tractors Dept. Faculty of Engineering, Minia University, Egypt.

Abstract
Proper forecasting is imperative in making production, marketing, and inventory decisions in many fields, especially in the automotive industry. Different quantitative analysis techniques were applied in this study to predict demands in automotive spare parts for inventory management. The study is applied on a service station of a transportation company where, due to the current financial constraints brought about by inflation, the company changed its ordering of spare parts from every two months to a monthly basis. This paper used twelve months of historical data to predict future values of the spare parts. Naïve, Moving Averages, Weighted Moving Averages, and Exponential Smoothing forecasting techniques were applied to predict the future values of spare parts. The results of each technique were compared which demonstrated that the Exponential Smoothing and Weighted Moving Averages can be used to deliver the most reliable predictions to help inventory optimization and strategic planning significantly. These two methods brought substantial improvements in forecast accuracy when applied to the studied case. They can be considered to be the key to operational efficiency and satisfying dynamic demand in the aftermarket of automotive spare parts.

Introduction

The automotive industry and its related sectors such as spare parts, depends heavily on accurate forecasting. These forecasts are the keys for making informed decisions about production, marketing, employment, and financial support[1]. They help to determine the annual sales, the types of cars to produce, and the necessary marketing efforts to increase sales. Predicting automotive sales patterns and quantities involve various methodologies, each offering distinct benefits and drawbacks. Numerous studies underscore the importance of quantitative analytical approaches such as time series analysis, regression analysis, and econometric modeling in forecasting automotive demands. These methods build models that link demand variables with input prices and other relevant factors, refining these relationships with historical data through error correction models[2, 3].

The automotive and spare parts industry face unique forecasting challenges due to its dynamic nature. Intense international competition, fluctuating government regulations, and capital constraints are some of these challenges. Demand in this sector is shaped by the diverse needs of buyers, manufacturers, retailers, and distributors, each contributing to the market dynamics[4, 5]. Accurate sales forecasts are vital for planning production schedules, managing raw materials and components, and optimizing production and warehousing resources. In marketing, effective forecasting helps determine costs, prices, delivery periods, and after-sales services, enhancing brand loyalty and reducing brand switching[6, 7].

Inventory management is another critical area where forecasting is crucial, particularly in industries where spare parts are essential for customer service and satisfaction[8]. The automotive spare parts market, characterized by low demand for individual stock-keeping units and a wide variety of products, requires accurate forecasting models to manage stock levels effectively. Precise forecasts help avoid stockouts, overstock, or redundant stock, optimizing inventory costs and improving service levels.

Choosing the right forecasting methods is not just a business decision but a strategic move to gain a competitive edge. Quantitative analysis, as the foundation of robust forecasting models, ensures a comprehensive approach that balances stock optimization with customer satisfaction[9, 10]. Given the complexities of the supply chain in the automotive and spare parts industry, forecasting is essential for maintaining competitive operations and supporting strategic business decisions[11, 12].

Petropoulos et. al [13] provided an overview of the forecasting methodology, focusing on theoretical underpinnings essential in practical applications. Therefore, it outlined some of the quantitative techniques for applying time series analysis and exponential smoothing with particular emphasis on how model selection and validation can improve the accuracy of the forecasts. Hoyle et al. [14] examined the perceptions of sales managers and salespeople regarding forecasting, establishing the importance of quantitative methods but equally concerned that practitioners relied on intuitive methods and experience, hence a gap in integrating the quantitative tools into everyday life practices. Tecnológico, [15], in his paper on demand forecasting models in marketing, went through various methods that grouped into statistical, judgmental, and combined methods and urged research into hybrid models. Armstrong et. al [16] provided evidence-based checklists for selecting methods to be used and implementing techniques, promoting best practices to improve reliability as much as possible. Again, Ingle et. al [17, 18] did a literature review on the different methodologies in demand forecasting using ARIMA and regression analysis but left room for future research on integrating those traditional methods with big data analytics. In their totality, these studies provide a strong base for understanding and developing how quantitative methods can improve sales and demand forecasting.

In this paper, we apply various quantitative forecasting techniques in predicting the demand for spare parts in the automobile industry. The case studied concerns a company that had been ordering its spare parts every two months but has lately changed to Per month due to the financial constraints amidst inflation.

In this study, we consider this firm's past 12 months of actual data to choose the 'best' method for forecasting demand. From this work, not only do we gain insight on practical differences in the numerous methods used to forecast, but at the same time, we understand the strategic insight they bring into effectively managing the spare parts inventory.

Quantitative Forecasting

Quantitative forecasting is a statistical method of forecasting where historical data are projection in the future for sales and trends. This procedure assumes that the future will resemble past conditions, so it is very suitable where stability exists and past data are available, as in the case of existing products or current technologies. Each of these methods is described sequentially in the following section, after which sampling and its application in forecasting are discussed. By removing human input in quantitative forecasting, through reliance on objective analysis of data, predictions thus made are more accurate[19]. There are numerous techniques applied in generating such forecasts, among which are time-series analysis and trend extrapolation. It is extremely useful in situations where robust historical data can be made available; however, this approach is constrained in case of new products or markets where past data is not available or not relevant.

Quantitative Forecasting Methods:

1. Naïve Approach

The Naïve Approach is a simple method of forecasting where the forecast for the next period is set equal to the actual value of the current period[20]. It assumes that the future values will be the same as the most recent observed value. Mathematically, if F_t if the forecast for time (t) and A_{t-1} if the actual value at time (t-1), then:

$F_t = A_{t-1}$

- F_t: Forecast for the current period (t)
- A_{t-1} : Actual value in the previous period (t-1)

2. Moving Averages

Moving averages reduce short-term oscillations to highlight medium- and long-term trends or cycles. It is calculated as the average of the data for the selected number of periods. It gets updated as new data becomes available. The formula for a simple moving average over (n) periods is[21]:

$F_t = \frac{A_{t-1} + A_{t-2} + .. + A_{t-n}}{n}$

- $A_{t-1}, A_{t-2}, .., A_{t-n}$: Actual values in the previous n periods
- n: Number of periods over which the average is calculated

3. Weighted Moving Average

Like the moving average, the weighted moving average gives more weight to each observation; however, it gives greater weight to the more recent observations[22, 23]. This is often done using the following formula for a weighted moving average:

$F_t = w_1 A_{t-1} + w_2 A_{t-2} + .. + w_n A_{t-n}$

- $w_1, w_2, .., w_n$: weights assigned to each actual value
- $\sum w_i = 1$: Sum of all weights equals 1

4. Exponential Smoothing

Exponential smoothing assigns exponentially decreasing weights as the observations become older. In other words, more weight is assigned to the more recent data points - the more time pass recent, the greater the weight[24]. The simple exponential smoothing equation is modeled as:

$F_t = \alpha A_{t-1} + (1 - \alpha) F_{t-1}$

- α: Smoothing constant between 0 and 1

These techniques, which each offer a unique way of using historical data to forecast future trends, are crucial tools in quantitative forecasting.

Methodology of Case Study

A case study was conducted in which the proposed inventory model was applied to a transportation fleet for a company. This company has a service station where total fleet repair and regular maintenance is done. Based on this, the application explains the policy of inventory to supply the maintenance department in the service center, which requires the necessary spare parts pertaining to periodic maintenance scheduling of the fleet. Earlier, the service center was placing orders every two months, that is, six purchase orders per year. Now, due to financial inflation and deficit, the decision maker decided to place orders once in a month, that is, twelve purchase orders per year. This necessitates that the demand for the next period should be predicted prior to every new period for the purpose of allocating appropriate funds.

Thus, the proper method of quantitative analysis needs to be found out, which would be applicable for forecasting the demand of the next period from the given historical data. In this section, real-world problem application of the proposed mathematical models in previous section are considered based on historical data of fast-moving items requiring spare parts for regular servicing at the service station of the car fleet. Table 1 shows the spare parts that the maintenance center needed during the previous 12 months - over the course of a full year.

Table 1: Spare parts that the maintenance center needed during the previous 12 months.

	Oil Filter	Spark Plug	Air Filter	Engine belt	Fuel Filter	brake pads
Period 1	70	130	40	20	90	370
Period 2	80	130	40	20	90	380
Period 3	80	135	45	25	100	400
Period 4	90	140	45	40	110	400
Period 5	80	150	40	30	100	370
Period 6	100	180	60	45	140	420
Period 7	105	170	50	30	100	470
Period 8	100	185	60	40	125	500
Period 9	65	140	35	25	100	480
Period 10	80	120	50	20	85	520
Period 11	70	140	40	30	90	375
Period 12	90	160	55	20	70	425

The approach which is applied to the case study is designed as a series of successive stages for the proper demand forecast and comparison of the applicability and effectiveness of various quantitative analysis techniques. The stages of the procedure are sequenced as follows:

Demand Forecast Calculation: It makes use of the historical data of the past series to find out the demand for the next period. All those quantitative analysis methods are made use of which can be applied for the forecast of demand for all types of spare parts. Because of this process, every aspect is taken into consideration regarding demand.

Deviation Analysis: Compute the squared deviations of the forecasted values with the actually observed values. The step thus measures the magnitude of accuracy for each technique representing how far the demand forecasted has deviated from the actually observed demand.

Calculation of Mean Square Error: Calculate the average squared deviation for each period to get the Mean Square Error. MSE thus formed would give the measure of overall accuracy for each technique. Since one of the methods does predictions only from the sixth period onwards, all the methods' MSEs will be computed from the sixth to the twelfth period. The method giving the smallest MSE will be the most accurate in predicting the demand for a certain type of spare part.

Ranking and Selection Method: Due to tremendous difference in the demand for various types of spare parts, the best forecasting method should be selected by ranking all types of methods against all types of spare parts. This process of ranking will be explained in detail in Table No. (9)

This will enable the use of the trend analysis the capability within Excel to build a visual for the forecasted demand for numerous future periods. It has to be taken into account that forecasts become more tenuous as the determined forecast period is projected further and further into the future, simply because it is based on projected data rather than historical data. This visual can help the decision-makers to come up with an initial order of magnitude estimate about future demand.

The structured approach allows for the proper selection of the most accurate forecasting method, but it also helps strategic planning due to the clear visualization of the variations of anticipated demand.

Tables 2 to 7 present the results of forecasting demand for each type of spare part for the period following the previously established intervals.

Note here that there could be two ways to compute the Moving Average Approach: one based on three previous periods and the other based on five previous periods. The Weighted Moving Average approach stipulates three periods with weights of 0.2 for the first period, 0.3 for the second period, and 0.5 for the immediate precedent period. For the Exponential Smoothing Method, the value for the smoothing constant α=0.5 was adopted.

Table 2: Forecasting Demand for Oil Filter

Oil Filter						
Period	actual	Naïve	Moving (3)	Moving (5)	weighted	exponential
Period 1	70					
Period 2	80	70				70
Period 3	80	80				75
Period 4	90	80	77		78	78
Period 5	80	90	83		85	84
Period 6	100	80	83	80	83	82
period 7	105	100	90	86	92	91
Period 8	100	105	95	91	98.5	105
Period 9	65	100	102	95	101.5	103
Period 10	80	65	90	90	83.5	84

Period 11	70	80	82	90	79.5	82
Period 12	90	70	72	84	72	76
		90	80	81	82	83

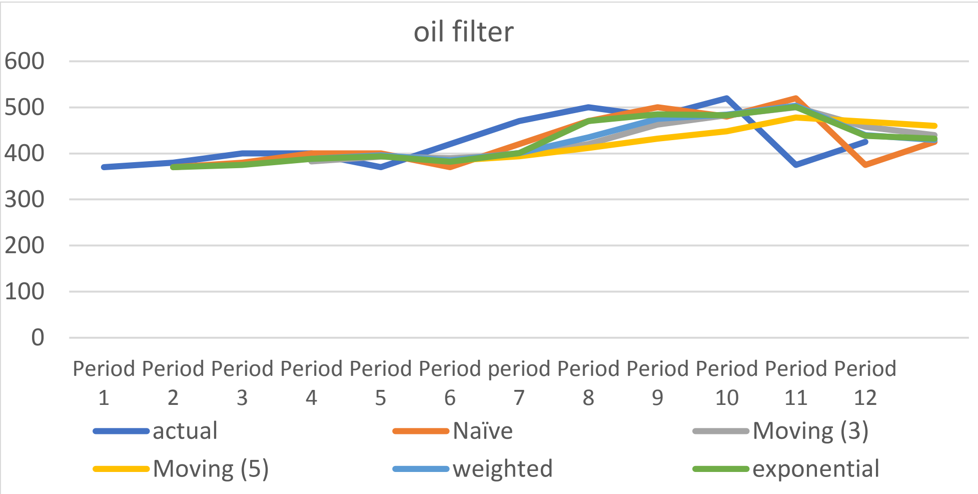

Figure1: Comparison Between Forecasting and Actual Demand for Oil Filter

Table 3: Forecasting Demand for Spark plug

Spark plug						
Period	actual	Naïve	Moving (3)	Moving (5)	weighted	exponential
Period 1	130					
Period 2	130	130				130
Period 3	135	130				130
Period 4	140	135	132		133	133
Period 5	150	140	135		137	136
Period 6	180	150	142	137	144	143
period 7	170	180	157	147	163	162
Period 8	185	170	167	155	169	170
Period 9	140	185	178	165	180	178
Period 10	120	140	165	165	160	159
Period 11	140	120	148	159	139	139
Period 12	160	140	133	151	134	140
		160	140	149	146	150

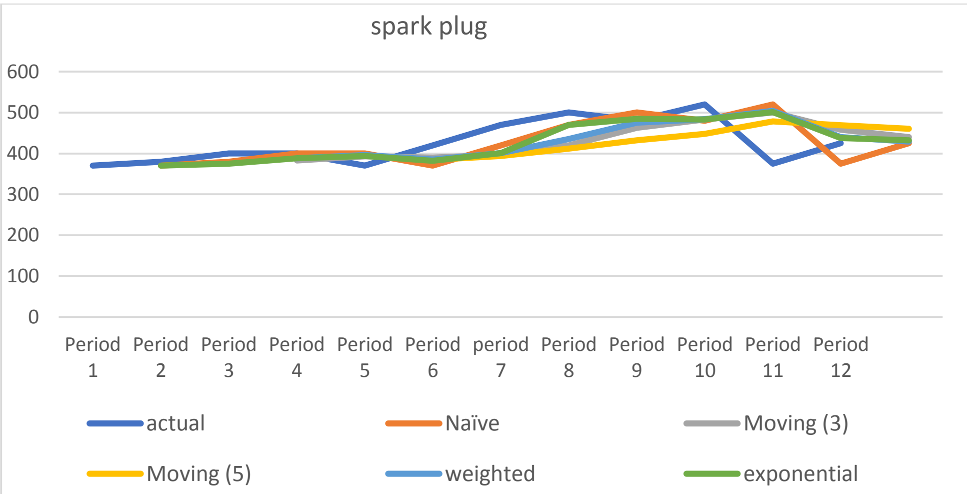

Figure 2: Comparison Between Forecasting and Actual Demand for Spark Plug

Table 4: Forecasting Demand for Air Filter

Air Filter						
Period	actual	Naïve	Moving (3)	Moving (5)	weighted	exponential
Period 1	40					
Period 2	40	40				40
Period 3	45	40				40
Period 4	45	45	42		43	43
Period 5	40	45	43		44	44
Period 6	60	40	43	42	43	42
period 7	50	60	48	46	51	51
Period 8	60	50	50	48	51	50
Period 9	35	60	57	51	57	55
Period 10	50	35	48	49	46	45
Period 11	40	50	48	51	48	48
Period 12	55	40	42	47	42	44
		55	48	48	50	49

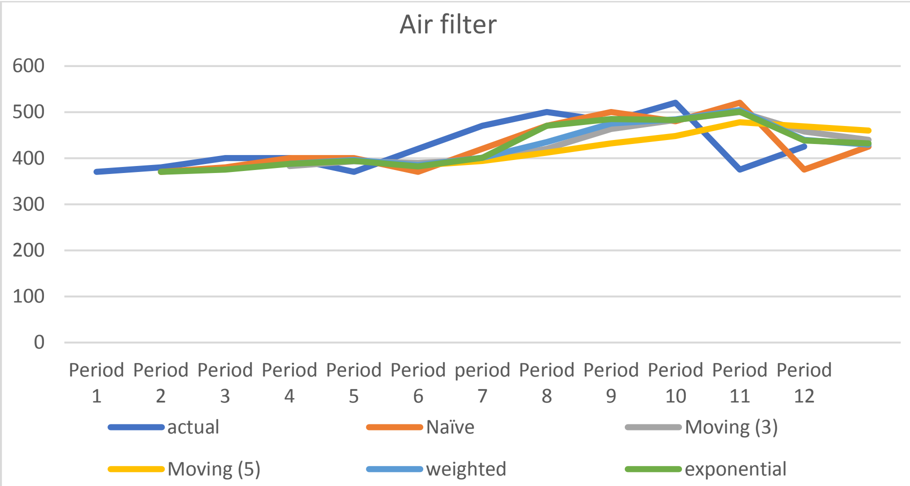

Figure 3: Comparison Between Forecasting and Actual Demand for Air Filter

Table 5: Forecasting Demand for Engine belt

Engine belt						
Period	actual	Naïve	Moving (3)	Moving (5)	weighted	exponential
Period 1	20					
Period 2	20	20				20
Period 3	25	20				20
Period 4	40	25	22		23	23
Period 5	30	40	28		32	31
Period 6	45	30	32	27	32	31
period 7	30	45	38	32	40	38
Period 8	40	30	35	34	35	30
Period 9	25	40	38	37	38	35
Period 10	20	25	32	34	31	30
Period 11	30	20	28	32	26	25
Period 12	20	30	25	29	26	28
		20	23	27	23	24

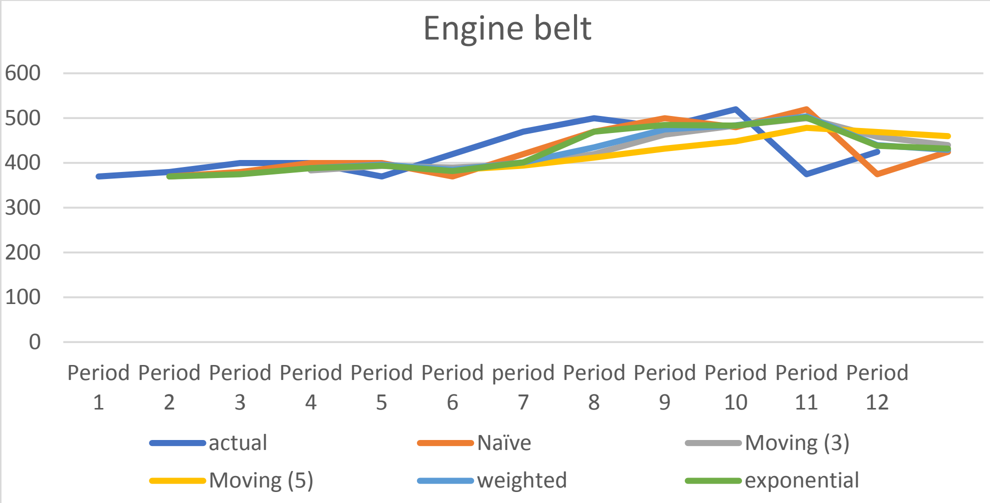

Figure 4: Comparison Between Forecasting and Actual Demand for Engine Belt

Table 6: Forecasting Demand for Fuel filter

Fuel filter						
Period	actual	Naïve	Moving (3)	Moving (5)	weighted	exponential
Period 1	90					
Period 2	90	90				90
Period 3	100	90				90
Period 4	110	100	93		95	95
Period 5	100	110	100		103	103
Period 6	140	100	103	98	103	101
period 7	100	140	117	108	122	121
Period 8	125	100	113	110	112	100
Period 9	100	125	122	115	120.5	113
Period 10	85	100	108	113	107.5	106
Period 11	90	85	103	110	97.5	96
Period 12	70	90	92	100	90.5	93
		70	82	94	79	81

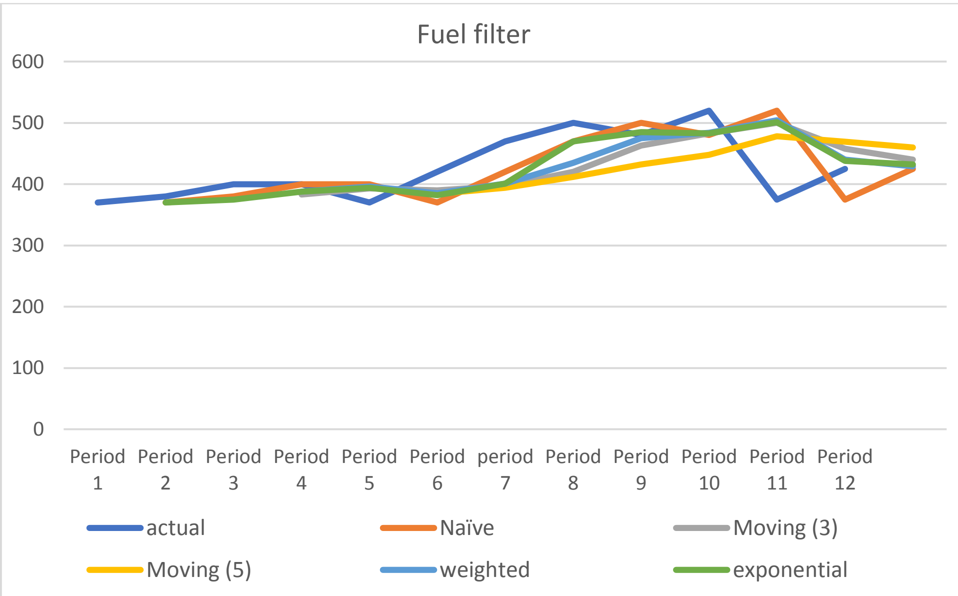

Figure 5: Comparison Between Forecasting and Actual Demand for Fuel Filter

Table 7: Forecasting Demand for Brake pads

Brake pads						
Period	actual	Naïve	Moving (3)	Moving (5)	weighted	exponential
Period 1	370					
Period 2	380	370				370
Period 3	400	380				375
Period 4	400	400	383		388	388
Period 5	370	400	393		396	394
Period 6	420	370	390	384	385	382
period 7	470	420	397	394	401	401
Period 8	500	470	420	412	435	470
Period 9	480	500	463	432	475	485
Period 10	520	480	483	448	484	483
Period 11	375	520	500	478	504	501
Period 12	425	375	458	469	440	438
		425	440	460	429	432

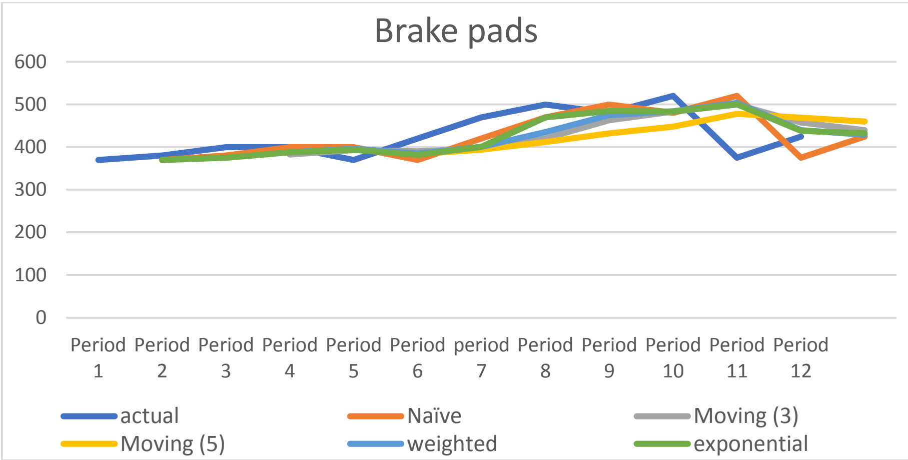

Figure 6: Comparison Between Forecasting and Actual Demand for Brake Pads

The square error for each period in each method means the square of the difference between the actual and predictive values. It was computed from those predictive values obtained from the previous tables using the different methods. After getting the square error for each period, a mean square error was calculated, shown in Table 8. The best method for prediction for each type of spare part was chosen based on this analysis. Note that the average values of mean square error calculations start from period number 6. This is because one of the methods had already started to make its first prediction from this period, hence ensuring the statistical validity and consistency of the results for all methods.

Table 8: MSE for Each Part by Each Method

	Naïve	Moving (3)	Moving (5)	weighted	exponential
Oil filter	342.8571	349.2063	325.4286	317	330.0502
Spark plug	635.7142857	894.0476	910	771.2143	710.9654
Air filter	253.5714	157.1429	132.2857	159.6786	148.1724
Engine belt	142.8571	87.69841	112.7143	89.28571	92.70368
Fuel filter	728.5714	488.4921	623.1429	489.2857	530.2595
Brake pads	4489.286	4433.73	4978.429	4054.75	3523.675

The main goal here is to find the best forecasting technique for the next period so that the decision maker can use. Since there is high difference between the forecasted values and actual demand for each spare part's type, it was not possible to directly calculate the arithmetic averages. Therefore, the ranking method has been used based on the calculated MSE.

Each forecasting method was ranked for each type of spare parts. The rank 1 was given for the method with better performance based on the MSE value, ranks 2 through 5 for the rest of the methods. After that the total rank for each forecasting method was calculated. The method with the lowest cumulative rank is considered the most reliable for the decision maker. Table 9 shows the ranking process and the results.

Table 9: Ranking process for each forecasting method with respect to spare parts.

	Naïve	Moving (3)	Moving (5)	Weighted	Exponential
Oil filter	4	5	2	1	3
Spark plug	1	4	5	3	2
Air filter	5	3	1	4	2
Engine belt	5	1	4	2	3
Fuel filter	5	1	4	2	3
Brake pads	4	3	5	2	1
Total	**24**	**17**	**21**	**14**	**14**

From the above table we can notice that both methods, Exponential Smoothing, and Weighted Moving Average Approach, of 3-periods gives the lowest total values. Therefore, α and preset weight prefer more reliable predictions to the institution. Hence, these methods are recommended for the decision maker. The Naïve approach method should be totally avoided since its predictions are far away from the actual values.

Result Analysis

The case study delved into the application of various quantitative forecasting techniques in a transport fleet company's service station, aiming to arrive at the demand forecast for spare parts. The context was a maintenance center that used to frequently service and repair, but due to increased financial inflation and limited budget, the frequency had to be shifted to once a month. This shift underscored the need for more accurate demand forecasts to ensure proper allocation of funds for spare parts procurement.

The analysis started with the Naïve method, which forecasted demand based on past trends of actual values in the previous period. Much as it is simple, the method was found to be inadequate because of its high deviation from the actual demand, hence an excellent forecasting error. In the Naïve approach, forecasts are usually far from actual values due to the simplicity of the technique, making it less reliable for strategic inventory management.

The following technique would be applied: Moving Averages in variations of 3-period and 5-period. It reduced the short-term fluctuations and gave medium to long-term trends. Even while the approach smoothed data, large error margins were still observed compared to actual demand. This model proved to be better than the Naïve approach but still not accurate enough for optimal inventory planning.

The more recent observations in the Weighted Moving Averages model had greater weights, improving the accuracy of the resulting forecasts. Using weights 0.2 for the first period, 0.3 for the second period, and 0.5 for the immediately preceding period, this technique could capture recent trends in the data better than its alternative techniques like the Naïve and simple Moving Averages Approach. Hence, it yielded more reliable predictions than either technique. The Weighted Moving Averages did better, especially regarding their correspondence of the forecasted demand with the actual demand for many spare parts categories.

Exponential Smoothing is another technique that gave the best results in this study. This technique gives exponentially decreasing weights to older data points. Using a smoothing constant α of 0.5, this method gave high weights to recent data and, therefore, captured the most recent trends. On average, methods under Exponential Smoothing return a minor mean square error, reflecting the accuracy of the forecast when computing future demand. It turned out that these were good cases of constant series in history, hence giving an accurate and reliable forecast.

This study's finds the significant superiority of Exponential Smoothing and Weighted Moving Averages methods over other types of demand forecasting for the automotive spare parts industry. These two methods provide the reliable predictions necessary for informed decisions in inventory and financial planning. The Naïve method, while simplistic, did not perform well, and the Moving Averages Method, while slightly better, still fell short of the required accuracy.

This case study underscores the practical necessity of applying proper forecasting methods to navigate the dynamic and complex market for automotive spare parts. The accurate forecasts obtained through exponential smoothing and weighted moving averages significantly contribute to optimizing inventory levels, reducing costs, and ensuring the timely availability of spare parts.

Conclusions

Accurate demand forecasting is essential in the automotive industry, particularly in sectors like spare parts, which play a paramount role in inventory management. Although some simple methods, such as Naïve, would provide somewhat simplistic forecasts in this paper, more complex methods like Exponential Smoothing and Weighted Moving Averages were necessary for better accuracy. These methods proved to be the most reliable in predicting future demand for the firm, thus aiding it in optimizing its inventory management and keeping operational efficiency within financial constraints. The results show the importance of business enterprises adopting advanced quantitative forecasting methods so that they can be run competitively and allow strategic decisions on an informed basis.

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